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Review Article

# Artificial intelligence in doctoral training: Bridging gaps, easing burdens

Gerardo Alfredo Rodríguez [a], Andres Chiappe [a,*], Julio Durand [b]

[a] Universidad de La Sabana, Colombia
[b] Universidad Austral, Argentina

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ABSTRACT

In an era when artificial intelligence is reshaping knowledge, doctoral education faces structural and institutional pressures that jeopardise retention. This systematic review, complemented by a reflective thematic synthesis, identifies early-stage researchers' main barriers and examines how AI's promises might address them. Following PRISMA, we analysed 92 articles using thematic synthesis alongside descriptive frequency mapping. Five major barrier categories emerged: mental health and well-being; academic supervision; personal factors (including work–life balance, financial constraints, and motivation); academic skills; and institutional factors (including work organisation). Findings indicate AI offers support through personalised learning, intelligent assistance, and task automation. The study informs educational leaders, supervisors, and researchers pursuing hybrid supervision, evidencing AI's transformative potential in advanced academic training.

## 1. Introduction

The Fourth Industrial Revolution is reconfiguring how knowledge is produced and learned, as artificial intelligence (AI), data analytics, and connected digital infrastructures become embedded in educational practice (Molla & Cuthbert, 2019). Within this shift, Education 4.0 increasingly refers to learning ecosystems that combine hybrid delivery with real-time feedback, adaptive guidance, and data-informed decision-making (Vargas et al., 2024). Consequently, AI is moving from being an optional enhancement to becoming part of the operating conditions of contemporary education, shaping participation, pacing, feedback, and the organisation of learning activities across platforms and modalities (Freigang et al., 2018; Nwokocha et al., 2025). This transformation raises a direct question for advanced academic training: how can doctoral education remain rigorous and humane while doctoral candidates are expected to work, learn, and produce research within AI-saturated environments?

### 1.1. *The social relevance of doctoral formation: from scientific excellence to societal contribution*

Doctoral education sits at the intersection of scientific excellence and societal contribution, as early-stage researchers are expected to generate new knowledge while engaging ethically with fast-evolving technological and policy landscapes (Ha Choi et al., 2021; Molla & Cuthbert, 2019). At the same time, doctoral cohorts are increasingly diverse, including working professionals and international students who must sustain high autonomy under substantial cognitive and emotional demands (Migliore, 2024; Pavlik, 2015). In principle, AI could strengthen doctoral support by expanding access to timely feedback, scaffolding complex tasks, and enabling more flexible learning pathways. Yet these possibilities are unevenly realised across programmes, and they often remain disconnected from the practical realities that shape doctoral persistence and attrition. In this way, AI becomes not only a research instrument but a scaffold for academic resilience and success.

As mentioned by Freigang et al. (2018), despite its transformative potential, doctoral education remains fraught with persistent and emerging barriers. These range from limited access to funding and mentorship to psychological challenges such as anxiety and burnout. Many of these difficulties are exacerbated by rigid institutional structures and a lack of personalised academic support. However, AI offers promising avenues to mitigate such issues. In this regard, Barrera Castro et al. (2024) point out that through learning analytics, AI can identify patterns of disengagement, predict risk of dropout, and recommend tailored interventions in real time.

Nevertheless, the integration of AI into doctoral education is still in its early stages. Rodríguez Flores and Sánchez Trujillo (2025) note that while undergraduate and professional training benefit from AI-driven systems, doctoral programmes often lack the infrastructure and pedagogical frameworks to fully leverage these technologies. This gap

* Corresponding author.
*E-mail addresses:* gerardo.rodriguez1@unisabana.edu.co (G.A. Rodríguez), andres.chiappe@unisabana.edu.co (A. Chiappe), jdurand@austral.edu.ar (J. Durand).

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reflects broader structural inequalities and underscores the need for deliberate, ethically grounded implementation of AI in advanced academic contexts. Moreover, as Hurtado et al. (2024) note, the study of doctoral barriers often remains fragmented. A more holistic approach, one that includes digital and technological dimensions, is essential to design effective and equitable support mechanisms that respond to the multifaceted nature of the doctoral experience.

Despite extensive research on doctoral attrition and candidate experience, evidence about barriers is frequently reported in fragmented ways, and work on AI in doctoral education is often discussed separately from the realities of doctoral persistence and support (Hurtado et al., 2024; Sverdlik et al., 2018). In this regard, Barrera Castro et al. (2024) and Rodríguez Flores and Sánchez Trujillo (2025) mention that this separation limits institutional decision-making: programme leaders and supervisors may recognise the pressures doctoral candidates face, while still lacking an integrative account of where AI can plausibly help, under what conditions, and with what trade-offs. Accordingly, this PRISMA-guided review synthesises literature from the last decade to consolidate the main barriers reported for early-stage doctoral researchers and examine how AI-enabled approaches are being proposed or used to reduce their impact. In doing so, we aim to provide an evidence-informed basis for designing doctoral support that is both technologically responsive and pedagogically defensible.

At the same time, AI-enabled support introduces non-trivial risks that must be acknowledged from the outset: biased outputs may disadvantage certain fields, languages, or communities; efficiency gains can shift supervisory work towards verification rather than formative dialogue; unequal access to infrastructure can widen participation gaps;

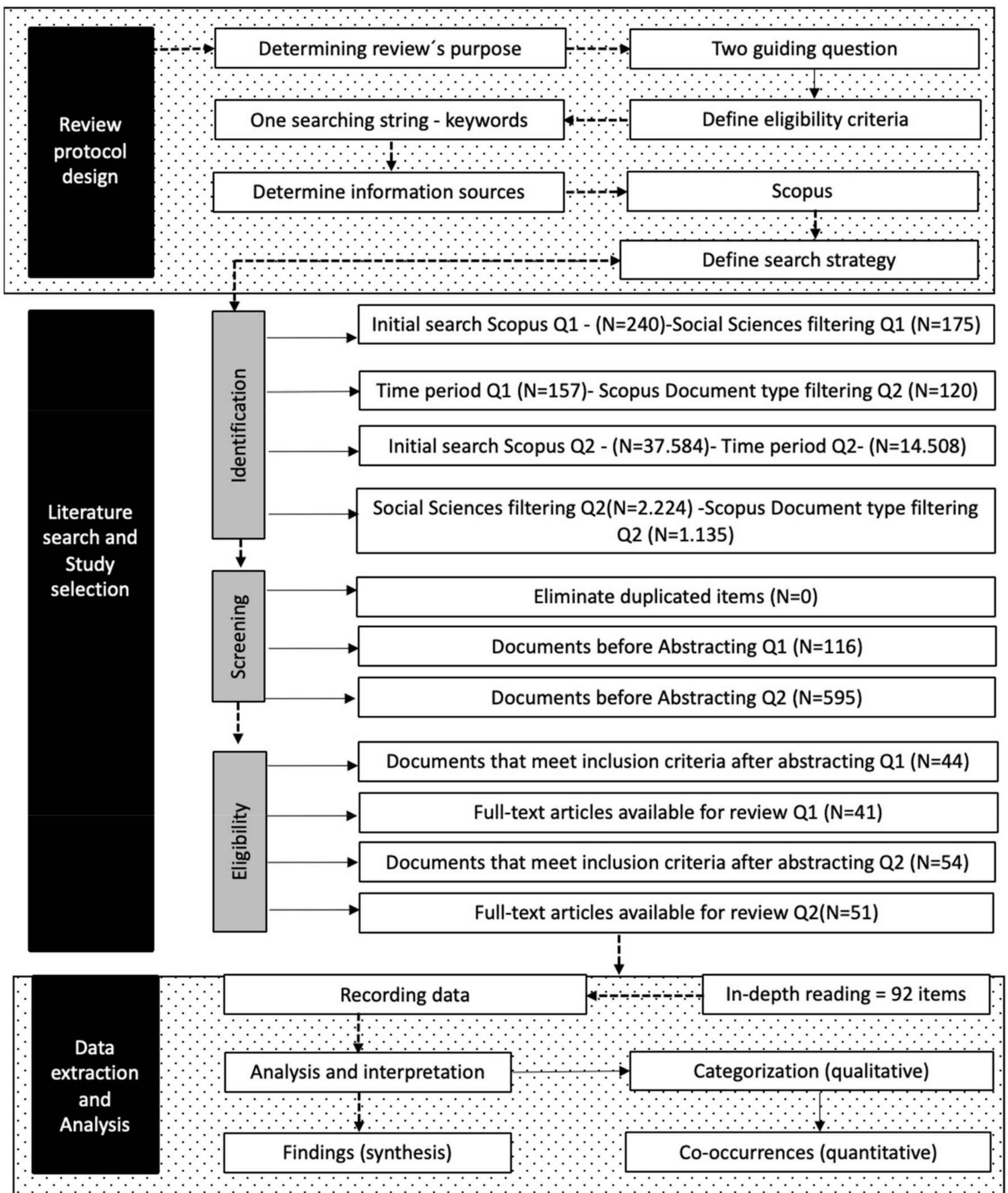


**Fig. 1.** PRISMA-guided review design and analytic workflow.

generative errors can erode academic rigour if left unchallenged; and data practices raise unresolved issues of privacy, consent, and governance (Baker & Hawn, 2022; Helm et al., 2024). For these reasons, we treat "responsible use" as part of the analytic frame, foregrounding human-in-the-loop oversight, operational transparency, and data-responsible policies as enabling conditions rather than afterthoughts (Mandinach & Gummer, 2021). This stance positions the contribution of the review as deliberately bounded: it maps where AI support is educationally plausible, and where claims should be tempered by context.

## 2. Method

This study was conducted as a PRISMA-guided systematic review (Okoli, 2015). While the search, screening, and reporting stages followed systematic-review conventions, the synthesis was intentionally reflective and interpretive, using thematic synthesis alongside descriptive frequency mapping to integrate heterogeneous evidence across contexts. The process encompassed the phases of identification, screening, eligibility assessment, and synthesis. This procedure allowed for a comprehensive exploration of the existing body of knowledge and the identification of relevant publications amidst a vast information landscape. As illustrated in Fig. 1, the review employed two parallel search strategies, each addressing a specific guiding research question.

### *2.1. Review protocol design*

In this article, "protocol" refers to the pre-specified and auditable set of decisions that governed searching, screening, eligibility, and extraction. The term does not imply a clinical-style trial protocol; rather, it operationalises transparency and reproducibility in the review process. The "reflective" dimension is confined to the interpretive stage of thematic synthesis, where findings are integrated to generate propositions and implications.

The initial phase focused on the conceptual and procedural planning of the review, structured around two central research questions:

What are the main barriers encountered by early-stage doctoral researchers?

How can artificial intelligence contribute to reducing the impact of these barriers?

To guide the inquiry, we first defined the purpose and scope of the review, formulated inclusion/exclusion criteria, and selected Scopus as the primary data source. Scopus was chosen due to its comprehensive coverage, robust peer-review standards, and the availability of internal analytics tools that support advanced filtering and initial data interpretation (Adriaanse & Rensleigh, 2013; Airyalat et al., 2019).

### *2.2. Literature search and study selection*

For each research question, a tailored search string was developed and applied to the Scopus database.

- Q1 Search string (barriers to doctoral formation): TITLE-ABS-KEY (("doctoral students" OR "PhD candidates" OR "PhD researchers") AND ("barriers" OR "challenges" OR "difficulties" OR "obstacles") AND ("supervision" OR "mental health" OR "academic stress" OR "PhD experience"))
- Q2 Search string (AI in education): (("artificial intelligence" OR "AI" OR "machine learning") AND ("doctoral education" OR "PhD education" OR "doctoral programmes" OR "doctoral studies") AND ("implementation" OR "integration" OR "use" OR "adoption"))

For both searches, a multistage filtering process was conducted using Scopus's internal tools. Filters included subject area (Social Sciences), time period (2015–2025), and document type (articles). Below, Table 1 shows the results for each search.

**Table 1**
Filtering results for Research Question 1.

| Filter Applied | Results |
|---|---|
| Initial search | 240 |
| Social Sciences | 175 |
| Time period | 157 |
| Document type (articles) | 116 |
| After abstract screening | 44 |
| Full-texts included | 41 |

#### *2.2.1. Inclusion and exclusion criteria*

To render the selection logic fully auditable, we pre-specified eligibility criteria using a structured review-framing framework (Population/Problem, Phenomenon, Context, Design, and Outcome) to ensure consistent screening across heterogeneous study types, previously applied on educational research and other research fields (Fajardo-Ramos et al., 2025), as a PCC framework variation (Chan et al., 2024; Perle et al., 2025), and applied them at both title/abstract and full-text stages. Conceptually, PPCDO extends established question frameworks used in evidence synthesis for qualitative/mixed-methods retrieval, while following PRISMA guidance on declaring a priori eligibility criteria and documenting reasons for exclusion (Aromataris, 2020; Cooke et al., 2012). Accordingly, each screening decision carried an explicit PPCDO reason and is summarized in the PRISMA flow (Page et al., 2021).

For Q1 (barriers to doctoral formation), the *Population/Problem* targeted doctoral students or candidates across disciplines, especially at early stages, while excluding undergraduates, master's students, postdoctoral samples, or supervisor-only reports. The *Phenomenon* had to be the explicit identification, characterization, or explanation of barriers (e.g., supervision, mental health, workload, funding, integration); papers concerned solely with distal career outcomes or generic policy commentary without empirical linkage to training barriers were excluded. Regarding *Context*, only higher-education doctoral training (on-campus, online, or hybrid) was eligible; non-HE or purely administrative settings were not. In *Design*, empirical qualitative, quantitative, or mixed-methods studies, as well as systematic/scoping reviews synthesizing barriers, were eligible, whereas editorials, non-systematic essays, books, and abstract-only items were not. As *Outcomes*, barriers needed to be central (measured outcomes, thematic categories, or explanatory mechanisms), not incidental mentions. This operationalization mirrors PCC-style specification of eligibility in complex educational reviews and aligns with qualitative question frameworks that foreground phenomenon and context (Booth et al., 2021).

For Q2 (artificial intelligence in doctoral education), the *Population/Problem* encompassed doctoral students, supervisors, or doctoral programmes; records reporting only non-doctoral data were excluded. The *Phenomenon* required documented use, implementation, or adoption of AI-personalisation/recommendation, automation/analytics, or intelligent assistance (e.g., tutoring, writing support, dashboards); generic "digital" tools without AI components or purely theoretical ethics pieces without doctoral-education implications were excluded. In *Context*, the focal processes had to concern doctoral learning, supervision, research training, or programme-level development; purely administrative uses were out of scope. Regarding *Design*, eligible studies included experiments/quasi-experiments, surveys, case studies, design-based research, and implementation reports with evaluative data, as well as systematic/scoping reviews; tool descriptions without evaluation and data-free conceptual essays were excluded. As *Outcomes*, studies had to report adoption, effectiveness/benefits, risks, or conditions of use within doctoral education; purely technical performance metrics unrelated to learning or supervision were excluded. Tailoring eligibility in this way follows contemporary recommendations to adapt question frameworks to educational synthesis and to register explicit criteria before screening (Tricco et al., 2018).

Following this screening, 544 articles were excluded, resulting in 51 studies selected for in-depth analysis, as shown in Table 2.

### 2.3. Data extraction and analysis

To secure reproducibility, the extraction protocol was developed before full screening and then refined through piloting. The instrument, a structured spreadsheet, captured bibliographic data, and PPCDO-aligned fields tailored to each research question (e.g., barrier categories for Q1; AI functionality and adoption conditions for Q2). We first piloted the instrument to verify clarity and coverage; based on this calibration, definitions were tightened (for example, distinguishing *automation/analytics* from *intelligent assistance*), and validation rules were added to prevent coding drift (Okoli, 2015; Page et al., 2021).

Because interpretive depth and reliability were both essential, we adopted a hybrid coding strategy. Deductive codes reflected the PPCDO architecture and the review questions, while inductive codes emerged from iterative reading of the corpus. Code definitions, inclusion/exclusion rules, and canonical examples were compiled into a codebook that guided all subsequent decisions (Guest et al., 2011; Mezmir, 2020). Inter-coder agreement on the presence/absence of top-level themes was estimated across themes and double-coding was made whenever new inductive themes were introduced (Landis & Koch, 1977).

Analytically, we combined thematic synthesis with descriptive frequency counts in order to balance interpretive richness and transparency of prevalence. Following Braun and Clarke's (2006) phases, codes were iteratively organized into candidate themes, contrasted through constant comparison, and then refined into an integrative structure: for Q1, barriers were organized across individual, interpersonal, institutional, and systemic layers; for Q2, AI uses were organized into personalisation, automation/analytics, and intelligent assistance, each examined with enabling conditions and risks (Thomas & Harden, 2008). To avoid over-interpreting frequency as effect size, counts are reported as indicators of distribution rather than as measures of impact (Sandelowski, 2001).

### 2.4. Study quality appraisal and confidence grading

To increase transparency and interpretability, we appraised the methodological quality of each included study using design-appropriate checklists (Hong et al., 2018). Following the recommendations of Thibault (2022), two reviewers independently rated each study against the relevant criteria and resolved discrepancies through adjudication meetings. Ratings informed, but did not mechanically determine, the synthesis.

We then assigned a confidence grade to each thematic claim: High, Moderate, or Low, based on the quality of contributing studies, consistency across findings, adequacy of the evidence base (scope and depth), and directness with respect to our review questions. Also, confidence grading was conducted at the theme level and is reported alongside the synthesis to signal where claims are well-supported and where caution is warranted.

**Table 2**
Filtering results for Research Question 2.

| Filter Applied | Results |
|---|---|
| Initial search | 37,584 |
| Time period | 14,508 |
| Social Sciences | 2224 |
| Document type (articles) | 1135 |
| After abstract screening | 595 |
| Full-texts included | 51 |

## 3. Results

This PRISMA-guided systematic review seeks to identify and synthesise the primary barriers faced by doctoral researchers and, in parallel, to examine how current AI-enabled approaches are being positioned to address them. These barriers are closely linked to the development, or lack, of essential competencies, either by amplifying existing difficulties or creating new ones. Five major categories of barriers were identified, as shown in Fig. 2.

The first relates to mental health and well-being, with high prevalence of stress, anxiety, and depression (Glorieux et al., 2025; Schwoerer et al., 2021), as well as issues of self-perception such as impostor syndrome (Berry et al., 2020; Sverdlik et al., 2020) and academic isolation (Castelló, McAlpine, & Pyhältö, 2017). The second involves doctoral supervision, particularly the quality of the supervisor-student relationship (Beasy et al., 2021; Cotterall, 2013) and the clarity and usefulness of feedback (Borders et al., 2020; Leijen et al., 2016).

The third barrier concerns personal factors, including work-life balance and financial constraints that constrain sustained engagement (Levecque et al., 2017; Rizzolo et al., 2016). Within this category, the literature also highlights motivational dynamics as a proximal mechanism shaping persistence and withdrawal (Litalien & Guay, 2015). The fourth barrier involves academic skills, particularly writing and research capacity, whose deficits slow progress and increase vulnerability to attrition (Conway, 2011; McAlpine & McKinnon, 2013). The fifth barrier concerns institutional factors, including programme structures, resources, and governance conditions that shape doctoral trajectories (Hurtado et al., 2024); notably, work organisation and time-allocation demands emerge here as a recurrent institutional pressure that interacts with supervision and performance regimes (Acharya et al., 2024).

### 3.1. Mental health and well-being barriers

Mental health and well-being have become increasingly central in discussions about the doctoral journey. As highlighted by Sverdlik et al. (2020), these issues play a critical role in students' persistence and success. In a large-scale study, Larcombe et al. (2022) found that 26.3% of doctoral candidates cited mental health, particularly stress, depression, and anxiety, as the primary reason for attrition.

Comparable findings emerged in other national contexts. In Belgium, 32% of doctoral students reported mental health issues (Levecque et al., 2017), while in France, 51% experienced stress, 42% anxiety, and 54% depression during their doctoral studies (Casey et al., 2023). These data underscore a widespread concern that transcends geography.

A major contributing factor is the academic culture of overwork, which fosters isolation and often leads to psychological distress (Teng et al., 2024). This environment can exacerbate emotional vulnerability, especially among students with limited support systems or those juggling academic and personal responsibilities.

This review identifies mental health not only as a personal concern but as a systemic challenge within doctoral education. Stress, anxiety, and depression are not isolated phenomena, they are deeply embedded in the structural and cultural conditions of the academic ecosystem.

#### 3.1.1. Barriers related to stress, depression, and anxiety

Stress is widely recognised as a harmful psychological state closely linked to compromised mental health and well-being. Recent studies have highlighted its disproportionate prevalence among doctoral students (Beasy et al., 2021). In this context, Zhou and Mollo (2023) found that graduate students are more likely to experience depression and anxiety than the general population. Similarly, Schwoerer et al. (2021) observed that over 35% of doctoral students felt unable to manage their academic lives at least once a week, with 25% experiencing daily stress. Moreover, 52% reported mental exhaustion weekly, and 22% felt overwhelmed at least once a week. These results suggest that stress is not

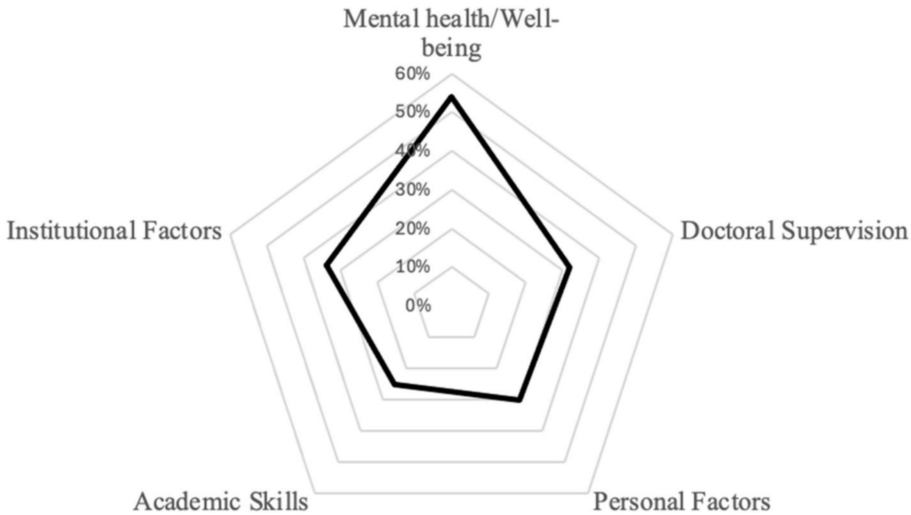


**Fig. 2.** Five major categories of barriers in doctoral training identified in the review.

sporadic but systemic. In this context, supervisory power imbalances, lack of support mechanisms, and a sense of dependence emerge as significant contributing factors (Glorieux et al., 2025). In addition, poor mentoring relationships further increase vulnerability to depression and anxiety (Ueno et al., 2025).

Beyond interpersonal dynamics, external stressors also play a critical role, such as financial constraints, family obligations, and professional demands, which are often exacerbated by limited academic support and dehumanizing institutional processes, intensify emotional strain (Beasy et al., 2021). In support of this, Hurtado et al. (2024) identified personal stressors such as health issues, unmet expectations, time conflicts, and burnout as frequent challenges faced by doctoral students.

Moreover, Byrom et al. (2022) indicated that cognitive and emotional factors also contribute to mental distress and emphasized the impact of self-doubt, fear of failure, and low confidence, with 63% of students reporting these issues during their doctoral journey. Likewise, Sverdlik et al. (2020) highlighted impostor syndrome as a significant amplifier of stress and depressive symptoms.

Finally, Berry et al. (2020) argued that excessive ambition, often cultivated within the academic environment, leads to overwork and mental health crises. Students with pre-existing vulnerabilities, such as certain personality traits or past traumas, are at heightened risk. Likewise, systemic issues such as limited funding and excessive responsibilities are frequently cited as triggers for depression (Acharya et al., 2024; Ueno et al., 2025). In addition, difficulties with doctoral writing have also been shown to evoke strong emotional responses and sustained stress (Castelló, Pardo, et al., 2017; Kokotsaki, 2023).

#### 3.1.2. Barriers related to self-perception and identity

Self-perception and academic identity are critical psychological dimensions that significantly shape doctoral students' experiences. Cotterall (2013) argues that academic prestige is deeply linked to one's sense of self-worth, dignity, and perceived competence, which are themselves tied to recognition, status, and reputation. However, many students develop negative self-perceptions when comparing themselves to peers, often leading to feelings of inadequacy and self-doubt (Bothello & Roulet, 2019; Jandrić, 2022).

A particularly salient manifestation of these issues is impostor syndrome, defined by Sverdlik et al. (2020) as the fear of being exposed as a "fraud" and the inability to internalize success. Moreover, Byrom et al. (2022) indicate that this condition is associated with distorted self-assessment, low self-esteem, and exacerbated feelings of isolation and anxiety. Similarly, Glorieux et al. (2025) note that a perceived tension between autonomy and structural ambiguity can deepen insecurity and foster impostor syndrome. Students often feel pressured to embody the role of an "expert" without adequate support, especially under the "publish or perish" culture (Bothello & Roulet, 2019).

Additionally, the development of academic identity plays a crucial role. Sverdlik et al. (2018) define academic identity as how students see themselves within scholarly communities. McAlpine and Amundsen (2013) distinguish between individual and collective identity, shaped through interaction with peers and supervisors. This identity is closely tied to academic work, institutional role, and envisioned career path. However, recurrent self-doubt, fear of criticism, and uncertainty about belonging to academia can undermine this process (Fernandez et al., 2019; Skakni, 2018), leading to persistent feelings of incompetence and exclusion.

#### 3.1.3. Barriers related to loneliness and isolation

Loneliness is defined as the perceived lack of meaningful social connections or the subjective evaluation of insufficient social resources (Jandrić, 2022). Within the doctoral context, several factors contribute to isolation, including academic competition, transient professional relationships, and the absence of informal social bonds (Berry et al., 2020). Regarding this, Castelló, McAlpine, and Pyhältö (2017) found that 20% of doctoral attrition cases were linked to socialization difficulties, especially strained relationships with supervisors and research teams.

Moreover, doctoral students often experience more profound loneliness than the broader academic community, a situation closely tied to limited departmental visibility and inadequate institutional resources (Berry et al., 2020; Ueno et al., 2025). Also, Ortega-Jiménez et al. (2021) associate this phenomenon with psychological inflexibility, rigid behavioural patterns that hinder adaptive coping.

This sense of detachment can lead to disengagement from the research community. As Abdelghaffar and Eld (2025) note, uncertainty, solitude, and the expectation of autonomous work complicate doctoral students' integration into academic life. Ultimately, persistent isolation may result not only in diminished motivation but also in increased risk of dropout (Castelló, Pardo, et al., 2017).

### 3.2. Barriers related to doctoral supervision

Supervision is one of the most influential factors in doctoral success, yet also one of the most cited sources of dissatisfaction. In a study by Larcombe et al. (2022) involving 152 participants, 88% reported supervision-related difficulties, and 22% noted a lack of interest from their supervisor. Across the 37 articles reviewed, three main supervision-related barriers emerged: the student-supervisor relationship, the quality of academic and research guidance (i.e., feedback), and the personal impact of supervisory dynamics, findings consistent with Sverdlik et al. (2018).

Several authors emphasize the negative consequences of unclear expectations and weak supervisory engagement. Cotterall (2013), Glorieux et al. (2025), and Sverdlik et al. (2018) describe these situations as a form of "negative freedom," marked by lack of structure, limited interaction, and insufficient support. Supervisors play a key role in cultivating either a sense of belonging or isolation (Castelló, Pardo, et al., 2017).

In addition, Beasy et al. (2021) and Acharya et al. (2024) indicate that time constraints are another major obstacle, compounded by lack of intellectual commitment or expertise in key areas such as methodology and critical thinking. Often, supervisors are assigned without proper matching criteria, resulting in poor communication and misaligned expectations (Berry et al., 2020; Rizzolo et al., 2016). Feedback-related issues are also widespread. Similarly, Kokotsaki (2023) and Borders et al. (2020) report feedback that is vague, delayed, or overly critical. In some cases, feedback lacked structure or was too general to be actionable.

### 3.3. Barriers related to personal factors

#### 3.3.1. Family–work balance

Among the most significant personal barriers faced by doctoral students is achieving a sustainable balance between academic responsibilities and family life. Several studies have identified this tension as a critical factor influencing stress, demotivation, and dropout. Borders et al. (2020) highlight how family obligations and financial strain often hinder research concentration. Similarly, Larcombe et al. (2022), in a study with 1017 participants, found that 12% cited family pressure as a reason for discontinuing their doctoral studies.

Balancing personal and academic priorities frequently requires trade-offs that can lead to disruption and distress (Sverdlik et al., 2018). This is echoed by Rizzolo et al. (2016), where 64% of respondents and 38% of focus group participants reported difficulty managing family and professional roles. Interviews by Acharya et al. (2024) further revealed challenges related to caregiving responsibilities involving children, partners, or elderly parents.

Levecque et al. (2017) identified work–family conflict as a major source of stress contributing to attrition. Similarly, Castelló, McAlpine, and Pyhältö (2017) found that 25% of their Spanish sample ($n = 724$) withdrew due to work–life imbalance. The issue was especially pronounced among part-time students, 51.6% of whom reported serious difficulty reconciling personal life with academic demands, compared to 26% of full-time students and 60% of those working outside academia.

Furthermore, an unsupportive academic culture that stigmatizes leaving the lab early can exacerbate imbalance and emotional strain (Fernandez et al., 2019). However, support from supervisors and institutional structures significantly enhances students' ability to manage these demands (Hurtado et al., 2024; Schwoerer et al., 2021).

#### 3.3.2. Financial constraints and funding issues

Financial hardship is a major barrier for many doctoral students, often requiring them to take on paid employment that reduces their availability for academic work and contributes to emotional distress (Beasy et al., 2021). Regarding this, Hurtado et al. (2024) classify employment instability, economic dependence, and low income as key socio-economic risk factors for dropout, which are further exacerbated by academic-related expenses such as research costs and publication fees.

Similarly, Larcombe et al. (2022) report that 13% of participants in their study cited financial pressure as the second leading cause of doctoral attrition, after mental health concerns. Similarly, Rizzolo et al. (2016) reported that 17% of survey respondents and 31% of focus group participants identified financial insecurity as a major obstacle.

For their part, Castelló, McAlpine, and Pyhältö (2017) found that 23% of students had no income and only 21% received scholarships. Still, 18% reported funding difficulties, particularly related to insufficient scholarships. Related to this, Leijen et al. (2016) confirm that many students are unable to leave their jobs to focus on their studies due to inadequate stipends. Consequently, self-funding often forces students to postpone or abandon personal goals such as marriage, housing, or healthcare (Acharya et al., 2024).

#### 3.3.3. Motivational dynamics

Within the broader category of personal factors, the reviewed studies foreground motivational dynamics, both intrinsic and extrinsic, as a key determinant of persistence and dropout.

Motivation, both its presence and absence, is a critical determinant of doctoral persistence and dropout. In this regard, Borders et al. (2020) and Litalien et al. (2015) identify internal motivations such as intellectual growth, interest in the field, and research curiosity as key drivers of engagement. In contrast, external motivations include career prospects, academic recognition, and degree attainment (Syed Mohamed et al., 2020).

With respect to motivation, Castelló, McAlpine, and Pyhältö (2017) found that 19% of doctoral students reported motivation-related issues, with career uncertainty emerging as a prominent source of demotivation. Social factors such as family support, peer collaboration, and the quality of supervision can also influence motivational levels. According to Litalien and Guay (2015), when doctoral advisors and students develop complementary roles, students report greater autonomy and competence, leading to higher success rates, an observation echoed by Acharya et al. (2024).

Conversely, students who perceive their academic environments as unsupportive tend to feel less competent and more inclined to withdraw. In this sense, lack of programme support structure forces students to rely heavily on self-motivation, which is further challenged by unclear research goals or reduced interest (Borders et al., 2020). Moreover, Sverdlik and Hall (2020) also note that working students and parents tend to depend more on external motivators, but sustaining high motivation over time becomes increasingly difficult.

### 3.4. Barriers related to academic skills

The review identified academic skills as a significant barrier within the doctoral experience, with three main subcategories emerging: writing proficiency, data collection and analysis skills, and self-efficacy. One of the key issues highlighted by Castelló, McAlpine, and Pyhältö (2017) and Leijen et al. (2016) was the perceived lack of competence among doctoral students. These self-perceptions are often shaped not only by individual limitations but also by broader structural conditions. For example, Sverdlik et al. (2018) suggest that inconsistent institutional procedures and overly high supervisory expectations may contribute to students' feelings of inadequacy regarding their academic performance.

#### 3.4.1. Writing skills

Writing proficiency emerged as a significant sub-barrier in doctoral education. For instance, McAlpine and McKinnon (2013) found that 37% of students reported needing writing support from their supervisors. In addition, Castelló, McAlpine, and Pyhältö (2017) identified several maladaptive beliefs, such as procrastination, perfectionism, and the notion that writing is an innate ability, that frequently hinder students' academic progress. These beliefs, often triggered by emotional fatigue or burnout, are compounded by a lack of confidence and can lead to prolonged writer's block (Kokotsaki, 2023).

Moreover, difficulties in academic writing are not only cognitive but also structural. In this regard, Acharya et al. (2024) and Leijen et al. (2016) emphasized that many doctoral students lack adequate training in preparing academic manuscripts, making the publication process time-consuming and discouraging. Feedback from reviewers, rather than being constructive, was often perceived as confusing or demotivating. Likewise, qualitative data from Gimenez et al. (2024) revealed recurring themes such as "difficulty expressing ideas", "feeling one's output isn't good enough" and "believing there's nothing important to say". Furthermore, Cotterall (2013) noted that the time-consuming nature of writing, especially in a second language, adds further stress, particularly when combined with reading and comprehension difficulties in English.

#### *3.4.2. Research capacity*

In addition to writing challenges, limited research capacity emerged as another critical academic barrier. In this context, Borders et al. (2020) reported a mismatch between students' research skills and doctoral expectations, expressing a gap between what the students know and what they need to know. Specifically, students struggled with narrowing their research focus, formulating realistic questions, and selecting appropriate methodologies. This was further complicated by difficulties in finding research teams aligned with their interests.

Similarly, Castelló, McAlpine, and Pyhältö (2017), King and Williams (2014), and Larcombe et al. (2022) observed that students experienced challenges across multiple stages of the research process, particularly in design, data collection, and analysis. According to Leijen et al. (2016), a lack of methodological training often resulted in poorly constructed or constantly changing research designs.

Furthermore, Conway (2011) highlighted major deficiencies in information literacy. His study revealed that many postgraduate students were unable to identify core academic resources, select appropriate search strategies, or understand citation conventions. For instance, among a sample of 41 students, 59% could not choose a relevant search method, and 33% were unable to identify a Boolean operator. Collectively, these deficits not only delay research progress but may also increase the likelihood of attrition, especially in fields with high methodological demands.

### *3.5. Barriers associated with institutional factors*

Institutional conditions represent a critical dimension in doctoral student retention. According to Hurtado et al. (2024), institutional barriers are the second most influential factor in doctoral attrition, accounting for 13% of cases. Glorieux et al. (2025) identified funding shortages and performance-based indicators, particularly publication pressure, as key institutional constraints that reduce students' research autonomy. These findings are consistent with results presented by Borders et al. (2020) and Beasy et al. (2021).

Similarly, Sverdlik et al. (2018) emphasize that well-structured departments foster autonomy by offering clear orientation, accessible supervision, and internal research networks. Conversely, the absence of such structures often results in excessive bureaucracy and procedural ambiguity (Castelló, Pardo, et al., 2017). Moreover, several studies (Acharya et al., 2024; Beasy et al., 2021; Castelló, McAlpine, & Pyhältö, 2017) highlight additional institutional challenges, including inadequate research resources, vague programme requirements, and a lack of organisational consistency.

#### *3.5.1. Work organisation*

Within the institutional factors category, work organisation and time allocation repeatedly appear as structural constraints shaping doctoral progress and well-being. Glorieux et al. (2025) point out that work organisation plays a crucial role in doctoral students' ability to manage their academic journey. In this regard, they explain that gaining autonomy over how and when time is allocated is vital, not just for flexibility in location, but for prioritizing research-related tasks. However, tension often arises between autonomy and the absence of structure, particularly when students lack supervisory guidance or face institutional performance pressures.

Similarly, Kokotsaki (2023) highlights problems maintaining a regular writing rhythm, especially among students balancing work and study. This is echoed by Castelló, McAlpine, and Pyhältö (2017), who observed that part-time students often struggle with extreme fatigue and work–life imbalance.

Additionally, Blalock et al. (2023) report that working students face ongoing challenges reducing their workload, making it harder to meet deadlines and maintain research momentum. Time management becomes even more complex considering the multiple demands placed on doctoral students: selecting a topic, conducting literature reviews, mastering data analysis, teaching, publishing, and writing a dissertation (Acharya et al., 2024).

Considering these organisational barriers, artificial intelligence (AI) offers promising support. The review identified 49 recent studies addressing AI's "three promises": personalisation, assistance, and automation. Most frequently cited was personalisation, particularly AI-driven timely feedback (Carrillo Cruz et al., 2023; Kamalov et al., 2023), adaptive learning (Paredes Gallardo, 2024, pp. 512–539; Romero Alonso et al., 2024), and intelligent tutoring (Chen et al., 2025; Rojas & Chiappe, 2024).

Assistance was the second theme, with chatbots and writing tools enhancing students' daily and academic productivity (Smerdon, 2024; Álvarez-Herrero, 2024). Lastly, automation supported literature reviews, pattern recognition, and task scheduling (Medina Romero, 2023; Salas-Pilco & Yang, 2022; Tsaneva, 2025).

### *3.6. On the promises of AI integration in education*

To better understand how artificial intelligence may help address key barriers in doctoral training, this section outlines the main educational domains where AI has shown transformative potential. By identifying these domains, we can draw connections between specific AI capabilities and the previously discussed barriers.

#### *3.6.1. Personalisation through AI*

One of the most prominent domains regarding AI implementation in education is personalised learning. In this context, Carrillo Cruz et al. (2023) emphasize that advances in AI have enabled educators to identify students' individual needs during classroom activities, allowing for more tailored feedback and instructional planning. Several studies (Funda & Mbangeleli, 2024; Kamalov et al., 2023; Paredes Gallardo, 2024, pp. 512–539) underscore AI's capacity to deliver real-time, bias-free, individualised support and feedback.

Moreover, AI can provide holistic assessments of cognitive engagement and learning progression (Chen et al., 2025), enhancing logical reasoning and decision-making skills. AI systems can also detect risk factors and generate tailored academic plans, as shown by Romero Alonso et al. (2024), who describe co-intelligent tutoring systems that adapt to each student's learning profile.

Using extensive student datasets, including academic, socioeconomic, and behavioural indicators, AI can predict trends and provide timely interventions (Salas-Pilco & Yang, 2022). This enables personalised learning environments that adjust to students' pace and preferences, diagnose weaknesses (Bewersdorff et al., 2025; Prieto Andreu & Labisa Palmeira, 2024), and guide them through adaptive learning paths.

Finally, intelligent tutoring systems have demonstrated the most positive outcomes in improving reasoning and engagement (Wang et al., 2025), followed by learning platforms, generative AI, writing assistants, and formative assessment tools. In a recent survey, 70.4% of respondents agreed that AI has the potential to personalise education by adapting to individual learning needs (Ríos Hernández et al., 2024).

#### *3.6.2. Assistance through AI*

Artificial intelligence is increasingly used by students as a supportive tool to regulate academic efforts, ask questions, receive advice, and define next steps (Crompton & Burke, 2023). In this sense, Leite (2024) suggests reframing AI as "artificial assistance," noting that these systems do not generate original ideas but recombine existing ones, functioning as intelligent assistants.

From a research perspective, AI can enhance human intelligence and creativity. In this context, Lin (2023) argues that researchers should embrace large language models (LLMs) to boost productivity and innovation. Moreover, Smerdon (2024) reports that students use AI to support statistical analysis, hypothesis testing, and methodological structuring.

Additionally, AI is also proving valuable in supporting students' emotional well-being. Salas-Pilco and Yang (2022) note that AI can help identify symptoms of ADHD, anxiety, and depression. Similarly, Chen et al. (2025) highlight the integration of affective computing to offer adaptive feedback and emotional regulation strategies.

Overall, Álvarez-Herrero (2024), Leite (2024) and Panit (2025) report that generative AI chatbots are improving academic engagement by offering multilingual content, simulations for critical thinking, and personalised explanations. Similarly, Rubio et al. (2022) and Jo (2024) indicate that these technologies enhance communication, feedback quality, user experience and boost perceived efficiency, productivity, and academic performance.

#### 3.6.3. Writing through AI

Bolaños et al. (2024) point out that AI tools are increasingly used to enhance academic writing and highlight the application of natural language processing (NLP) to analyse texts and identify recurrent themes, as well as the use of ChatGPT to improve coherence and clarity. In this regard, Carrillo Cruz et al. (2023), in a study with 456 participants, found that 46.5% used ChatGPT to verify consistency in scientific writing, while 21.2% benefited from AI-based PDF readers, and 16.4% used AI to locate secondary resources. Furthermore, 10.7% reported using AI for paraphrasing and formal rewriting, findings also supported by Smerdon (2024), who notes the tool's utility in correcting grammatical errors and improving stylistic precision.

#### 3.6.4. Automation through AI

AI-driven automation significantly reduces workload and cognitive load (Morandini et al., 2023). In academic contexts, platforms like Monday.com and Asana help define deadlines and manage resources (Paredes Gallardo, 2024, pp. 512–539), while tools like Ad Astra support course planning and student tracking. AI can also automate content generation using NLP (Salas-Pilco & Yang, 2022).

In this regard, Bolaños et al. (2024) emphasize that AI can streamline article search and classification based on semantic vectors. Similarly, Tsaneva et al. (2025) highlight automated categorization using titles and abstracts, minimising manual validation. Moreover, platforms like Scopus and Dimensions are integrating LLM-based chatbots to assist with literature reviews (Medina Romero, 2023).

Additionally, AI supports project generation via tools like Smart. paperAI, which can draft research questions, hypotheses, and methodological frameworks. Graduate students increasingly use AI to manage large data sets, identify trends, and improve research accuracy (Rodríguez Flores & Sánchez Trujillo, 2025).

Besides the above, AI also aids in holistic evaluation through adaptive assessments and feedback systems (Chen et al., 2025). In administrative domains, automation streamlines resource allocation, scheduling, and student support (Liu et al., 2025; Álvarez-Herrero, 2024).

## 4. Discussion

A holistic view of education today reveals the growing opportunities enabled by digital technologies, particularly through automation, intelligent assistance, and personalised learning. As educational processes become increasingly digitalized, artificial intelligence and data science are reshaping the educational landscape (Freigang et al., 2018). This review highlights practical implications and suggests future research directions on how AI can mitigate doctoral training barriers by supporting emotional well-being, enhancing supervisory processes, and improving academic productivity.

### 4.1. Mental health and AI as emotional support

More than half of the reviewed studies on doctoral barriers reported symptoms of anxiety, depression, stress, and loneliness. These emotional states negatively impact academic writing, motivation, and persistence. In this context, AI tools, such as chatbots and intelligent assistants, can detect early signs of emotional decline through linguistic patterns, enabling adaptive and personalised responses (Chen et al., 2025; Salas-Pilco & Yang, 2022).

AI-supported writing tools also contribute to mental well-being by reducing impostor syndrome, improving document clarity, and easing workload pressures, especially in balancing academic, family, and employment responsibilities. While AI cannot replace clinical support, it offers scalable, accessible, and preventive emotional assistance for students in high-demand academic settings.

### 4.2. AI and supervisors: toward collaborative tutoring

Supervisory issues, such as lack of feedback, time constraints, and limited engagement, are among the most frequently reported doctoral challenges. These factors can lead to feelings of isolation, academic stagnation, and low self-esteem. In this context, AI can act as a complementary resource, supporting supervisors in providing timely and unbiased feedback (Parker et al., 2024). Thus, tools such as ChatGPT, SmartPaper.AI, and AI-powered editors can help structure ideas, clarify arguments, and enhance textual coherence, especially when supervisory access is limited. Moreover, AI-driven monitoring systems can flag signs of academic stagnation and suggest targeted interventions to both student and supervisor, fostering a hybrid tutoring model that combines human expertise with intelligent support (Bewersdorff et al., 2025).

### 4.3. AI as a life organizer

The results of this review show that doctoral candidates often juggle studies, employment, and family, creating organisational and cognitive overload. In this context, AI can be a strategic ally through the automation of routine tasks, such as literature reviews, data analysis, scheduling, and even draft writing (Bolaños et al., 2024). Platforms like Asana and Monday.com help organise thesis milestones and resources, while AI can detect workflow bottlenecks and propose personalised adjustments. Thus, automating these processes allows students to redirect energy toward intellectual work, which is especially relevant for part-time or non-traditional doctoral students, for whom AI creates viable pathways to research engagement beyond academia.

### 4.4. From correspondences to a generative explanatory frame

Gkintoni et al. (2025) suggest that the correspondences outlined above point out to a generative mechanism: AI support reconfigures where cognitive effort, pedagogical judgment, and data governance reside, and this redistribution mediates downstream outcomes. When outputs are legible and contestable, and when verification is proportionate, AI can amplify formative dialogue and planning; when criteria are opaque or verification is externalized, it can displace attention toward quality control and compliance (Rompczyk, 2025). These dynamics intersect with representation in training data and with institutional capacity, shaping whether personalisation expands or narrows students' perceived option space.

Two countervailing patterns are worth noting. On the one hand, Ahmed Langove and Khan (2024) note that automation intended to reduce workload may increase extraneous load if verification becomes systematic and time-consuming; the net effect depends on whether verification tasks are lightweight and targeted or heavy and pervasive. On the other hand, personalisation may constrain agency when recommendations appear prescriptive or when option sets are curated by under-representative data, even as it benefits students who need clearer scaffolds (Vallabhaneni et al., 2024). These patterns help explain mixed findings in the literature without appealing to incompatible theories.

### 4.5. Propositions for future testing and programme design

Across the evidence base, the five barrier domains identified in the review operate as *inputs* that shape the conditions under which doctoral researchers work and learn. These inputs include pressures related to well-being, supervision, personal constraints, academic skills, and institutional conditions, which interact rather than function in isolation. Therefore, the relevance of AI-enabled support depends not only on the presence of a given barrier but also on the configuration of conditions surrounding it (e.g., access, supervisory expectations, and programme governance).

Within this configuration, AI-enabled support can be understood through a set of *mechanisms* that may reduce friction in doctoral work while simultaneously creating countervailing demands. On the supportive side, mechanisms include scaffolding complex tasks, accelerating feedback cycles, automating low-level routines, and supporting planning and decision-making. Conversely, these gains can be offset by verification load, integrity monitoring, and governance requirements, particularly when institutional policies, training, and documentation practices are under-specified.

Finally, the above foregrounds the *outputs* that doctoral education ultimately values and that should guide evaluation of AI-enabled support: candidate well-being, persistence/retention, research productivity, supervision quality, and equity. Importantly, these outputs should be treated as conditional endpoints: the same mechanism can improve productivity while undermining well-being or equity if access, oversight, and accountability structures are weak. Accordingly, Table 3 reorganises the propositions for future testing and programme design into a structured format that clarifies their logic and practical use. Rather than presenting them as standalone claims, the table specifies for each proposition its core claim, the conditions under which it is expected to hold, and its implications for programme design and evaluation. This format is intended to support both empirical testing and institutional decision-making by making explicit the links between mechanisms, contextual boundaries, and actionable design considerations.

### 4.6. Risks, trade-offs, and conditions for responsible use

Building on the correspondences outlined above, the same mechanisms that allow AI to reduce cognitive and administrative load can also reassign where effort, judgment, and responsibility reside. Gains in speed and coverage can conceal a latent verification workload: as noted by Van Den Aker and Rahimi (2024), plausible yet imprecise outputs demand expert checking, and automated feedback pipelines may redirect attention from formative dialogue to quality assurance, an inversion that is especially salient in high-stakes doctoral milestones where validity and fairness are non-negotiable.

At the same time, as mentioned by Deed et al. (2014), personalisation reshapes the balance between responsiveness and agency. Adaptive recommendations are most effective when they remain legible and contestable; when criteria are opaque or overly prescriptive, the perceived option space narrows and developmental trajectories may drift toward what is convenient rather than what is educationally sound. Because model behaviour mirrors training data, these dynamics intersect with representation and equity: underrepresented fields, languages, and methodologies can receive systematically weaker guidance, making local expertise and critical scrutiny indispensable companions to algorithmic support (Maalsen, 2023).

Consequently, questions of data governance intensify these concerns. In this regard, Hoel and Chen (2018) highlight that analytics at scale rely on flows and aggregations that sit uneasily with data minimization, purpose limitation, and jurisdictional constraints. Furthermore, Frimpong (2025) indicates that in resource-constrained settings, outsourcing core AI services can harden technological dependencies and render portability of models, prompts, and datasets an institutional vulnerability. The calculus is therefore not merely technical but strategic: short-term capability gains must be weighed against long-term autonomy, continuity, and switching or decommissioning costs. Thus, what matters is not only whether AI is used, but how its role is made transparent, bounded, and educationally purposeful.

Accordingly, these intertwined risks point to conditions for responsible use that should be treated as design properties rather than external constraints. Thus, human-in-the-loop supervision needs to be specified, not assumed, with explicit, time-bounded roles for verification, acceptance, and refusal (Naser, 2025). In this regard, institutions should adopt data-responsible policies (minimization, retention, meaningful consent, portability) and, where context demands, consider local or federated processing to reduce exposure. Finally, targeted capacity-building for students and supervisors is essential so that AI augments, rather than replaces, the core practices of scholarly inquiry and academic mentorship.

As a result of the above, aligning these conditions with the patterns identified in the preceding synthesis enables the promise of AI to be reconciled with professional judgment, student agency, and justice in data practices.

**Table 3**
Propositions for future testing and programme design: claims, conditions, and implications.

| Proposition | Core claim | Main condition(s)/boundary | Implication for programme design or evaluation |
|---|---|---|---|
| Verification Load | AI-supported feedback is more likely to improve formative interactions when verification remains targeted and proportionate. | Explicit acceptance/refusal criteria; bounded checking routines. | Define verification protocols for students and supervisors; avoid diffuse checking burdens. |
| Agency Alignment | Personalisation is more likely to support self-regulation when students retain structured choice. | Transparent and contestable recommendation logic. | Require explainable recommendation practices and preserve student decision-making. |
| Equity by Representation | The risk of inequitable guidance increases when training data poorly represent the local disciplinary or linguistic context. | Strength of local expertise and critical review practices moderates risk. | Prioritise local validation, disciplinary calibration, and contextual oversight. |
| Governance-Autonomy Trade-off | Short-term gains from outsourced AI services can reduce long-term institutional autonomy. | Data minimization, portability, and continuity safeguards are absent. | Include portability and decommissioning criteria in procurement and policy decisions. |
| Integrity and Skill Formation | Over-reliance on AI in early stages can reduce opportunities for deliberate practice. | AI use is not bounded to metacognitive scaffolding and feedback literacy. | Define stage-appropriate AI uses that support, not replace, core scholarly skill formation. |
| Confidence–Use Coupling | Policy decisions should align with the confidence level of the evidence. | Theme-level confidence grading (High/Moderate/Low). | Scale high-confidence applications; keep low-confidence uses in pilot/evaluation mode. |

## 5. Practical implications

For doctoral researchers, the review suggests that AI-enabled support is most defensible when it functions as a scaffold rather than a substitute for core scholarly judgement. Accordingly, the value of AI lies in accelerating low-level bottlenecks, such as planning, drafting, and iterative refinement, while preserving the candidate's responsibility for argumentation, evidence selection, and conceptual integration. This positioning also implies a shift in self-regulation: candidates may need explicit routines for verification, citation checking, and reflective decision-making so that "efficiency" does not translate into reduced epistemic responsibility.

For supervisors, the findings point to a dual challenge. On the one hand, AI may reduce friction in feedback cycles and help candidates access timely guidance; on the other, it can increase the supervisory burden of verification and integrity monitoring if expectations are not clearly defined. Consequently, supervision practices may benefit from explicit agreements about acceptable AI use, transparent documentation of AI-supported steps, and feedback strategies that privilege reasoning, methodological clarity, and academic voice over surface-level correctness.

For programme leaders and institutions, the implications are primarily organisational and governance-related. If AI is to support doctoral progress equitably, institutions should invest in baseline access, training pathways for both candidates and supervisors, and coherent policies that address privacy, data governance, and academic integrity without defaulting to blanket prohibition. In addition, workload models may need revision, since AI can reshape where time is spent in the doctoral process, often moving effort from production to evaluation, verification, and accountability.

For developers and providers of AI-enabled academic tools, the review indicates that educational value depends on transparency and controllability. Tools that make sources, uncertainty, and constraints visible, and that facilitate auditable workflows, are more likely to align with doctoral education's standards than tools optimised solely for fluent output. Therefore, design choices that enable bounded assistance, traceability, and user oversight should be treated as pedagogical requirements rather than optional features.

## 6. Limitations

This review has limitations that should temper interpretation. First, the included studies are heterogeneous in design, context, and operationalization of both "barriers" and "AI support", which constrains comparability and limits the extent to which causal claims can be inferred. Second, database coverage and publication practices may have shaped the accessible evidence base, with a likely under-representation of non-indexed work and context-specific reports. Third, because AI capabilities and institutional policies are evolving rapidly, some empirical observations and tool-specific claims may become outdated, which reinforces the need to interpret the synthesis as a snapshot of an accelerating field.

## 7. Scope and transferability

The claims synthesised here are bounded by disciplinary mix, national systems, and institutional conditions, and they should be transferred cautiously across settings. Although the propositions provide a coherent map of where AI is plausibly supportive, and where risks cluster, implementation should be treated as a locally evaluated innovation. In practice, this implies piloting in bounded contexts, monitoring unintended consequences (including equity effects), and iteratively refining guidance before wider adoption.

## 8. Future research directions

Future studies should move beyond tool descriptions towards evaluative designs that test educationally meaningful outcomes, including well-being, retention, supervision quality, academic integrity, and equity. In addition, research should compare different governance and supervision models for AI use, examining how transparency, documentation practices, and verification routines shape doctoral learning rather than merely output productivity.

## CRediT authorship contribution statement

**Gerardo Alfredo Rodríguez:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Andres Chiappe:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Julio Durand:** Writing – review & editing, Writing – original draft, Conceptualization.

## Ethical statement

Ethical Approval is not applicable to this manuscript.

## Use of Generative AI

Generative AI was used only to improve grammar, clarity, and style. No content, analysis, or conclusions were generated by AI. The authors remain responsible for all text and its accuracy.

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Data will be available on request from authors.

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